MODELING FOR CRISIS MANAGEMENT OCCURRED DURING COMPUTER MEDIATED COMMUNICATIONS

Synopsis submitted in fulfillment of the requirements for the Degree of

DOCTOR OF PHILOSOPHY

IN

COMPUTER SCIENCE & ENGINEERING

By

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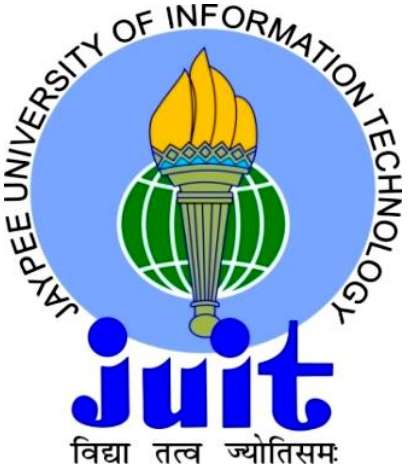

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ABSTRACT

Social Networks have become a very popular and instrumental procedure in all disciplines for analyzing the web of relationships at an organizational and societal level. This process is enabled by powerful computational skills and data mining techniques. The expertise of this analysis lies in identification of key individuals or groups in societal systems to detect and create network structures and to model its formation and growth.

The information diffused in the human population through randomly established networks, behaves similar to an epidemic spread. Distribution of people, occupying different positions in the network, have respective significance. The importance of positions in the network, number of connections and nature of connections, all together determine the metrics of the network. These metrics can further be formalized mathematically to reach to valuable insights.

In this thesis, we have made an effort to contribute effectively in the spread and control of crisis in online communication. We have mapped the epidemic model on social networks. Just like epidemic modeling is used to detect and control the spread of an epidemic, we have predicted the spread and control the of the social contagion. Social Contagion is anything that can spread in a population due to interpersonal influence, it can be information, norms, behavior, product adoption, common practices, opinions etc. Techniques can be applied to decipher a warning or early detection about adoption of any identifiable practice, norm or behavior in a population. Any information that is harmful to a high fraction of society and spreads through the networks of society is termed a crisis in social networks. Crisis management and control in social networks, has been achieved by addressing three major objectives.

Firstly, we have made an effort to map the epidemic model in the prediction of the crisis impact and spread with respect to time. Like any other disease epidemic, the various types of crisis can also be modeled as SIR , SIRS and other epidemic models .We have designed local epidemic models for individual committees and derived their dynamic schematics. These communities are modeled as clusters. Epidemics and crisis do not remain confined to one community. Therefore, we have designed a global community with an interconnection of local

communities. The global community represents the mechanism of crisis spread from one community to another community . After deriving the state transition matrix for the local and global epidemic models , we have done stochastic modeling to calculate the estimated time for the spread of the crisis from one stage to another .The degree of spread of the crisis, predicted with stochastic modeling enables us to identify crisis propagation .The proposed model also gives the predicted peak of epidemic occurrence and there after control laws are designed to control the crisis before it reaches uncontrollable proportions.

Secondly, the establishment of spread among connecting communities can be predicted in global community model. The migration of infectants from one community to susceptibles of another community can be analyzed through mathematical and computational algorithms, where the migrating infectants are clustered using modularity and spectral clustering techniques. Using these techniques, the outgoing migrants can be predicted and cleaved in order to prevent further spread of information leading to a crisis. In case if there is a connection between the infectants of one community and susceptibles of another community, isolation can be achieved by cleaving the nodes with high centrality.

Thirdly, the established social network is modeled as a weighted signal flow digraph. The information processing elements are used to compute the signal flow graph. The connected information processing elements are identified with the values of information inflow, information outflow and the diameter, which are integrated to form the signal flow digraph. . The proposed mathematical model is used for the identification of similar communities in the established network. The communities involved in the connected network are identified through the canonical form of social network. The communication from input to output mode is represented in the canonical form. From the digraph, the relationship between input and output is represented in the form of a transfer function which is calculated using Mason algorithm. The Jordan Canonical form helps us to identify the similar and dissimilar communities.

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CHAPTER1

INTRODUCTION

1.1*Problem statement*

The literature survey reveals that Social Network Analysis offers an opportunity to see the world through a network through a network paradigm. Learning to model and design these networks is central to 21st century science and engineering. It has great potential to offer. It is a game changer and we as computer scientists have to discover the flash points bubbling under the hood. With the computational and mathematical rules that govern how these networks are assembled, what are the defining rules and how they effect and operate our lives. The onus is on computer scientists to take advantage of the hidden insights and improve the way this world operates, not only understand the problem but to fix it. The interpretation of existing phenomenon, formulation of potential courses of action to reinforce the change in them is critical procedures applicable to any discipline and these are felicitated by immense social network data. The overarching goal of social network analysis can be achieved first by formalization of entities and relationships to represent the relational data, which is then followed by formulation of Social Network. The expertise of this analysis lies in identification of key individuals or groups in social systems to detect and create network structures and to model growth and pattern recognition analysis. The interpretation of existing phenomenon, formulation of potential courses of action to reinforce the change in the current phenomenon are critical procedures applicable to any discipline and these are felicitated by immense social network data.

In today's world, the humans are connected rapidly in a social network through IP enabled devices. Therefore, information flow is very fast in the randomly established social network. In this thesis work, we have found a similarity between the spread of social contagion and epidemic spread. Many researchers have tried to model these contagions using epidemic model. In the literature, the epidemic models are used to model the social contagion, but most of the work has been found with a closed system without any input or output. This thesis explores and solves the unique problem of social network analysis with epidemic mapping for both a closed system (local community) and interconnected systems (global

community). It is very difficult to tap or predict the dynamics of a rapidly changing social network. High degree of spread of social contagion may lead to a crisis. In such a scenario, a stochastic model is required to predict the spread and impact of a crisis with respect to time. With the prediction, the isolation algorithms are also important to cleave the migrants who may cause the crisis spread. Since many communities are involved in the formation of social networks so it is very important to identify the similar communities and their stability.

1.2 *Contributions*

This thesis includes several key contributions to the study and modeling for crisis management occurred during computer mediated communications in social networks.In view of the above discussion, the research problem was divided into three stages along with following objectives:

Stage I

i. Mapping of various epidemic models on social network

ii. Study of the dynamics of the mapped epidemic models, derived from state space equations

iii. Derivation of dynamics of local epidemic model and their interconnection in global community

iv. Stochastic Modeling of epidemic flow in local and global communities, for future prediction of information diffusion

v. Prediction of epidemic distribution vector using stochastic modeling

vi. Study of the various possibilities of global community formation using SIR-SIR-SIR, SEIR-SEIR-SEIR, SEIRS-SEIRS-SEIRS, and hybrid mapped communities

Stage II

i. Implementation of the various isolation algorithms to cleave the connection between the infectants of on community and susceptibles of other community

ii. Isolation of two communities using modularity clustering, for fast disconnection

iii. Isolation of two communities using spectral clustering, for slow disconnection

iv. Isolation of two communities using betweeness centrality and eigenvector centrality

v. Analysis of the dependency of separation constant with centrality measurement and isolation time

Stage III

i. Identification of various information processing elements
ii. Extraction of Information flow digraph as a combination of information processing elements
iii. Derivation of Jordan canonical form to identify similar communities
iv. Application of the control law for unstable communities with positive eigenvalue

This thesis embodies the subject matter resulting out of this study and is arranged in seven chapters.

1.3 *Outline of the Thesis*

The thesis has seven chapters out of which CHAPTER 1 presents Introduction. CHAPTER 2 presents literature of the epidemic, epidemic mapping on social networks, and social networks analysis. The preliminary notations are introduced to keep the clarity of usage throughout the thesis. CHAPTER 3 presents the efficient and fast algorithms to predict the impact and spread of crisis with time. The dynamics of the mapped epidemic models, derived from state space equations. CHAPTER 4 presents best control and manage of crisis by prevention of its further spread. Various isolation algorithms are used to cleave the connection between the infectants of one community and susceptibles of the other community CHAPTER 5 presents the identification of similar communities connected in a densely connected social network. CHAPTER 6 presents the study of nature of communication in social networks. Finally, CHAPTER 7 presents the conclusion of the thesis supported with the result of experiments and simulations followed by the future scope of the research work.

CHAPTER2

LITERATURE REVIEW

A brief introduction, epidemic models, social network analysis, centrality and clustering algorithms and tools used for social networks analysis in general has been described in thesis. History stands evidence that epidemics have had a catastrophic influence on mankind. Referencing a few major epidemics such as Black Death which had taken the lives of about one third of Europe's population, Yellow Fever in 1793 in USA and The Plague of Athens (430- 428) BC which took the lives of 1050 soldiers out of 4000 soldiers on an expedition Thucydides. A prominent feature of the above epidemics is that there was no reference of a person to person contagion. Only in the 19th century was it discovered that the cause of the disease spread was person to person contagion which gave rise to the concept of epidemic models. Networks and the epidemiology of infectious diseases have a very strong link connecting them. The epidemic models are based on individuals who have a finite set of contacts to whom infection can be passed, and a mixture of all such contacts form a network. The characteristics of networks improve understanding and prediction of epidemic patterns and preventive measures. Epidemic Models are based on compartmentalization of hosts. Analyzing a network requires knowledge of each individual and the relationships among individuals. Only those connections need to taken into consideration which describe relationships capable of transferring the infection. The main aim of epidemic modeling is to explore the factors that determine the incidence, spread and persistence of the epidemic. The transmission of the epidemic is determined factors such as infection prevalence, population, contact structure and probability of transmission.

Social Network has become a very popular and instrumental procedure in all disciplines for analyzing the web of relationships at organizational and societal level. This process is enabled by powerful computer skills and automated data collection techniques. The expertise of this analysis lies in identification of key individuals or groups in social systems to detect and create network structures and to model growth and pattern recognition analysis. The interpretation of existing phenomenon, formulation of potential courses of action to reinforce the change in them, are critical procedures applicable to any discipline and these are felicitated by immense social network data.

CHAPTER 3

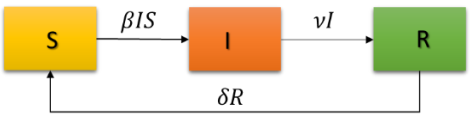
COMPUTATIONAL STOCHASTIC MODELING OF EPIDEMIC MAPPED SOCIAL NETWORKS

3.1.*Introduction*

In this chapter we have made an effort to predict the spread of crisis in online communication at any instance of time. This has been achieved by mapping the epidemic models on the social network [1-8]. A similarity has been identified in the spread of an epidemic and propagation of the social contagion. Social Contagion is anything that can spread in a population due to interpersonal influence, it can be information, behavior, common practices, opinions etc. Depending upon the conditions and situations, various forms of epidemic models are mapped. Once the dynamics of the social network are extracted in the form of an epidemic spread, the state space model is derived from the set of differential equations [9-15]. The state space matrix is considered as state transition matrix. Then the probability transition matrix is derived from Kolmogorov equations. The stochastic model is derived from the probability transition matrix and initial distribution vector. The stochastic model predicts the degree of spread of crisis at any instance of time. The proposed model is validated with real time data of EBOLA virus propagation. Various models are simulated and validated with different initial distribution vector.. In this chapter, all the models shown in Figure 3.1. are simulated and validated with different initial distribution vector.

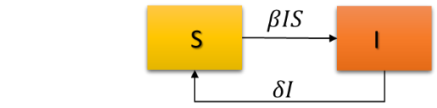
$$A=\begin{bmatrix} -\beta I & 0 & 0 \\ \beta I & -\nu & 0 \\ 0 & \nu & 0 \end{bmatrix}$$

(a)



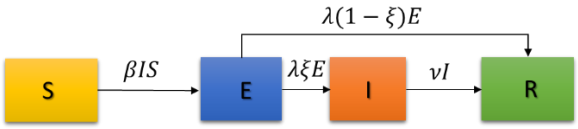
$$A=\begin{bmatrix} -\beta I & 0 & \delta \\ \beta I & -\nu & 0 \\ 0 & \nu & -\delta \end{bmatrix}$$

(b)



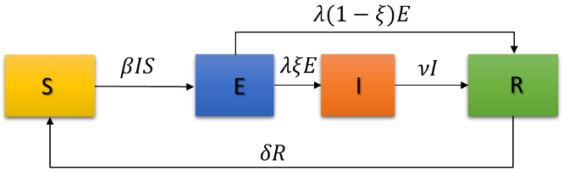
(c)

$$A=\begin{bmatrix} -\beta I & \delta \\ \beta I & -\delta \end{bmatrix}$$



(d)

$$A=\begin{bmatrix} -\beta I & 0 & 0 & 0 \\ \beta I & -\lambda & 0 & 0 \\ 0 & \lambda\xi & -\nu & 0 \\ 0 & \lambda(1-\xi) & \nu & 0 \end{bmatrix}$$



(e)

$$A=\begin{bmatrix} -\beta I & 0 & 0 & \delta \\ \beta I & -\lambda & 0 & 0 \\ 0 & \lambda\xi & -\nu & 0 \\ 0 & \lambda(1-\xi) & \nu & -\delta \end{bmatrix}$$

Figure 3.1: dynamic schematics of various epidemic models: (a)SIR, (b)SIRS, (c)SIS, (d)SEIR, (e)SEIRS

3.2. *Basic Epidemic Model*

The basic epidemic model consists of three stages, S susceptible, I infected and R recovered. The dynamics of these stages is given by equations (3.1 – 3.4)

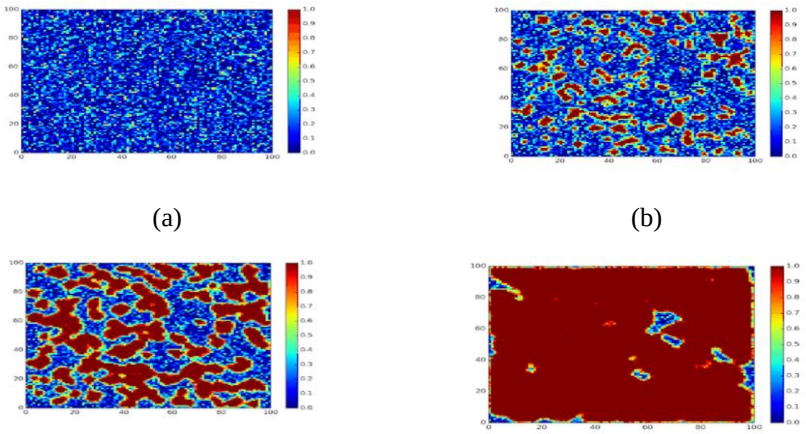
$$\frac{dS}{dt} = -\beta IS \tag{3.1}$$

$$\frac{dI}{dt} = \beta IS - \nu I \tag{3.2}$$

$$\frac{dR}{dt} = \nu I \tag{3.3}$$

$$N = S + I + R \tag{3.4}$$

Where β and ν are the flow rates between the stages



(a) (b)

(c) (d)

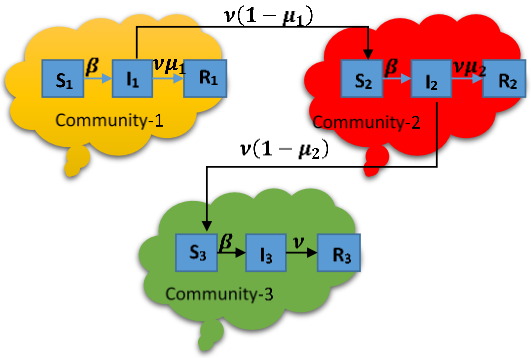
Figure3.2: stages of spread at time: (a) t, (b) t+Δt_1, (c) t+Δt_2, (d) t+Δt_3

$$\rho \equiv \frac{\nu}{\beta} \tag{3.5}$$

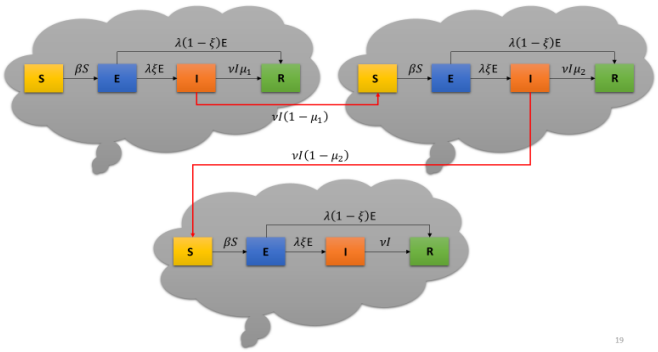
The linearization of model is done about the equilibrium points (S_e, I_e)

$$J = \begin{bmatrix} -\beta I_e & -\beta S_e & 0 \\ \beta I_e & \beta S_e - \nu & 0 \\ 0 & \nu & 0 \end{bmatrix} \tag{3.6}$$

3.3. *Epidemic Model of Global Community*



(a)



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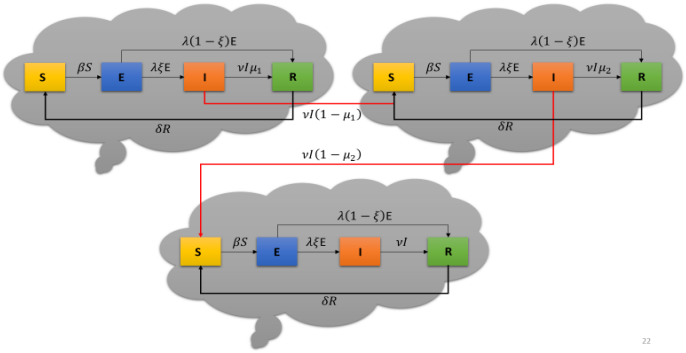
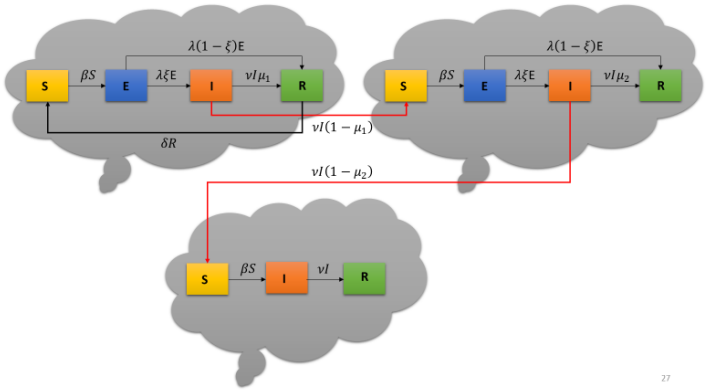


(c)



(d)

Figure 3.3: Intercommunity Clusters, (a) SIR-SIR-SIR (b) SEIR-SEIR-SEIR (c) SEIRS-SEIRS-SEIRS (d) Hybrid Mapped Communities

The dynamics of SIR-SIR-SIR model (Figure 3.3 (a)),are as follows:

$\frac{dS_1}{dt} = -\beta S_1$ (3.7)	$\frac{dS_2}{dt} = \nu I_1(1-\mu_1) - \beta S_2$ (3.10)	$\frac{dS_3}{dt} = \nu I_2(1-\mu_2) - \beta S_3$ (3.13)
$\frac{dI_1}{dt} = \beta S_1 - \nu I_1$ (3.8)	$\frac{dI_2}{dt} = \beta S_2 - \nu I_2$ (3.11)	$\frac{dI_3}{dt} = \beta S_3 - \nu I_3$ (3.14)
$\frac{dR_1}{dt} = \nu I_1 \mu_1$ (3.9)	$\frac{dR_2}{dt} = \nu I_2 \mu_2$ (3.12)	$\frac{dR_3}{dt} = \nu I_3$ (3.15)

$$N_{TotalPopulation} = N_{Community-1} + N_{Community-2} + N_{Community-3} \quad (3.16)$$

$$\dot{X}(t) = A_L X(t) \quad (3.17)$$

$$\begin{bmatrix} \dot{S} \\ \dot{I} \\ \dot{R} \end{bmatrix} = \begin{bmatrix} -\beta & 0 & 0 \\ \beta & -\nu & 0 \\ 0 & \nu & 0 \end{bmatrix} \begin{bmatrix} S \\ I \\ R \end{bmatrix} \quad (3.18)$$

3.4. *Stochastic Model for Epidemic Network*

Using Kolmogorov Equations [23]

$$A = \frac{1}{h}\left(P^T - I\right)$$

Where P represents the transition probability matrix and h is the transition time Hence $P = (I + hA)^T$. (3.19)

The initial Probability Transition Matrix is derived using equation (3.19) For the local epidemic, equation (3.18) becomes:

$$P_L = \begin{bmatrix} 1-h\beta & h\beta & 0 \\ 0 & 1-h\nu & h\nu \\ 0 & 0 & 1 \end{bmatrix} \quad (3.20)$$

Similarly, for the global epidemic,

1. SIR-SIR-SIR Global community:

$$A_G = \begin{bmatrix} -\beta & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \beta & -\nu & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \nu\mu_1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \nu(1-\mu_1) & 0 & -\beta & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \beta & -\nu & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \nu\mu_2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \nu(1-\mu_2) & 0 & -\beta & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \beta & -\nu & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \nu & 0 \end{bmatrix} \quad (3.21)$$

$$P_G = \begin{bmatrix} 1-h\beta & h\beta & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1-h\nu & h\nu\mu_1 & h\nu(1-\mu_1) & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1-h\beta & h\beta & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1-h\nu & h\nu\mu_2 & h\nu(1-\mu_2) & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1-h\beta & h\beta & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1-h\nu & h\nu \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad (3.22)$$

2. SEIR-SEIR-SEIR Global community:

$$A_G = \begin{bmatrix} -\beta & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \beta & -\lambda & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \lambda\xi & -\nu & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \lambda(1-\xi) & \nu\mu_1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \nu(1-\mu_1) & 0 & -\beta & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \beta & -\lambda & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \lambda\xi & -\nu & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \lambda(1-\xi) & \nu\mu_2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \nu(1-\mu_2) & 0 & -\beta & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \beta & -\lambda & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \lambda\xi & -\nu & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \lambda(1-\xi) & \nu & 0 \end{bmatrix} \quad (3.23)$$

$$P_G = \begin{bmatrix} 1-h\beta & h\beta & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1-h\lambda & h\lambda\xi & h\lambda(1-\xi) & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1-h\nu & h\nu\mu_1 & h\nu(1-\mu_1) & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1-h\beta & h\beta & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1-h\lambda & h\lambda\xi & h\lambda(1-\xi) & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1-h\nu & h\nu\mu_2 & h\nu(1-\mu_2) & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1-h\beta & h\beta & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1-h\lambda & h\lambda\xi & h\lambda(1-\xi) \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1-h\nu & h\nu \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

(3.24)

3. SEIRS-SEIRS-SEIRS Global community

$$A_G = \begin{bmatrix} -\beta & 0 & 0 & \delta & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \beta & -\lambda & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \lambda\xi & -\nu & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \lambda(1-\xi) & \nu\mu_1 & -\delta & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \nu(1-\mu_1) & 0 & -\beta & 0 & 0 & \delta & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \beta & -\lambda & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \lambda\xi & -\nu & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \lambda(1-\xi) & \nu\mu_2 & -\delta & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \nu(1-\mu_2) & 0 & -\beta & 0 & 0 & \delta \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \beta & -\lambda & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \lambda\xi & -\nu & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \lambda(1-\xi) & \nu & -\delta \end{bmatrix} \quad (3.25)$$

$$P_G = \begin{bmatrix} 1-h\beta & h\beta & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1-h\lambda & h\lambda\xi & h\lambda(1-\xi) & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1-h\nu & h\nu\mu_1 & h\nu(1-\mu_1) & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ h\delta & 0 & 0 & 1-h\delta & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1-h\beta & h\beta & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1-h\lambda & h\lambda\xi & h\lambda(1-\xi) & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1-h\nu & h\nu\mu_2 & h\nu(1-\mu_2) & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & h\delta & 0 & 0 & 1-h\delta & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1-h\beta & h\beta & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1-h\lambda & h\lambda\xi & h\lambda(1-\xi) \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1-h\nu & h\nu \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & h\delta & 0 & 0 & 1-h\delta \end{bmatrix}$$

(3.26)

3.5. *Calculation of Community Distribution Vector in Global Community*

For all flow rates = 0.01 and separation constant = 0.9, the probability transition matrix for local community is:

$$P_L = \begin{bmatrix} 0.99 & 0.01 & 0 \\ 0 & 0.99 & 0.01 \\ 0 & 0 & 1 \end{bmatrix}$$

The initial SIR distribution vector for N=510 is:

$[SIR]_L = [475 \quad 25 \quad 10]$ The distribution after 500 days:

$$[SIR]_{L500} = [SIR]_L (P_L)^{500} = [475 \quad 25 \quad 10] \begin{bmatrix} 0.99 & 0.01 & 0 \\ 0 & 0.99 & 0.01 \\ 0 & 0 & 1 \end{bmatrix}^{500}$$

$$[SIR]_{L500} = [SIR]_L (P_L)^{500} = [3 \quad 16 \quad 491]$$

Similarly, for global community:

$$P_G = \begin{bmatrix} 0.99 & 0.01 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.99 & 0.009 & 0.001 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.99 & 0.01 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.99 & 0.009 & 0.001 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.99 & 0.01 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.99 & 0.01 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

The initial distribution SIR vector for global community N=1530 is:

$[SIR]_G = [475 \quad 25 \quad 10 \quad 475 \quad 25 \quad 10 \quad 475 \quad 25 \quad 10]$

community distribution vector in global community are:

3.5.1 *Community Distribution for SIR Mapped Communities*

Table 3.2: The Variation of SIR Distribution Vector with Time

Time (Days)	SIR vector	Com.-1	Com.-2	Com.-3
100	$[SIR]_{G100} = [SIR]_G (P_G)^{100}$	[174 185 137]	[184 188 138]	[184 188 152]
200	$[SIR]_{G200} = [SIR]_G (P_G)^{200}$	[64 132 284]	[77 141 291]	[78 141 322]
300	$[SIR]_{G300} = [SIR]_G (P_G)^{300}$	[23 72 374]	[34 83 391]	[35 84 434]
400	$[SIR]_{G400} = [SIR]_G (P_G)^{400}$	[8 35 421]	[16 44 447]	[17 45 497]
500	$[SIR]_{G500} = [SIR]_G (P_G)^{500}$	[3 16 443]	[8 23 476]	[8 24 530]

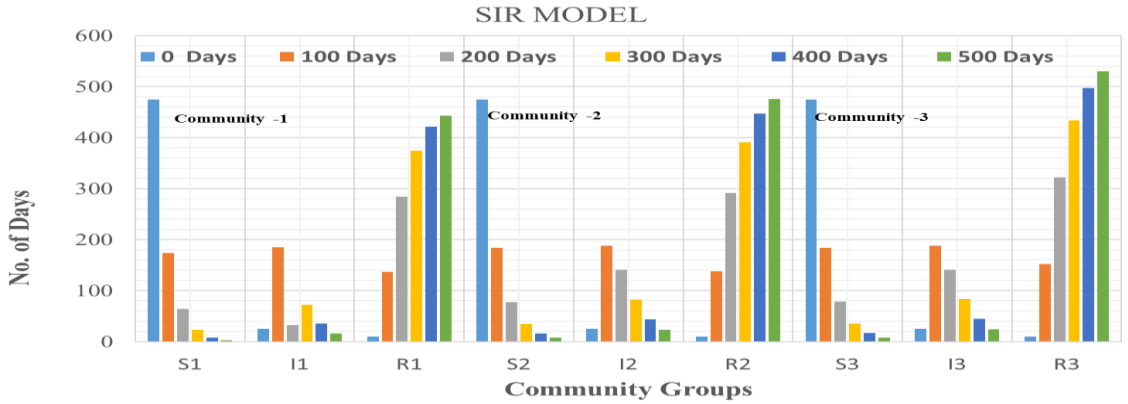


Figure 3.4: Community Distribution for SIR-SIR-SIR Mapped Communities

3.5.2 *Community Distribution for SEIR Mapped Communities*

Table 3.3: The Variation of SEIR Distribution Vector with Time

	S1	E1	I1	R1	S2	E2	I2	R2	S3	E3	I3	R3
0 Days	475	15	10	10	475	15	10	10	475	15	10	10
100 Days	174	181	50	102	176	182	50	102	176	182	50	105
200 Days	64	131	68	239	68	133	69	240	68	133	69	249
300 Days	23	71	55	345	29	76	56	349	29	76	56	364
400 Days	9	35	35	412	13	40	37	419	13	40	37	439
500 Days	3	16	20	448	7	20	22	460	7	20	22	483

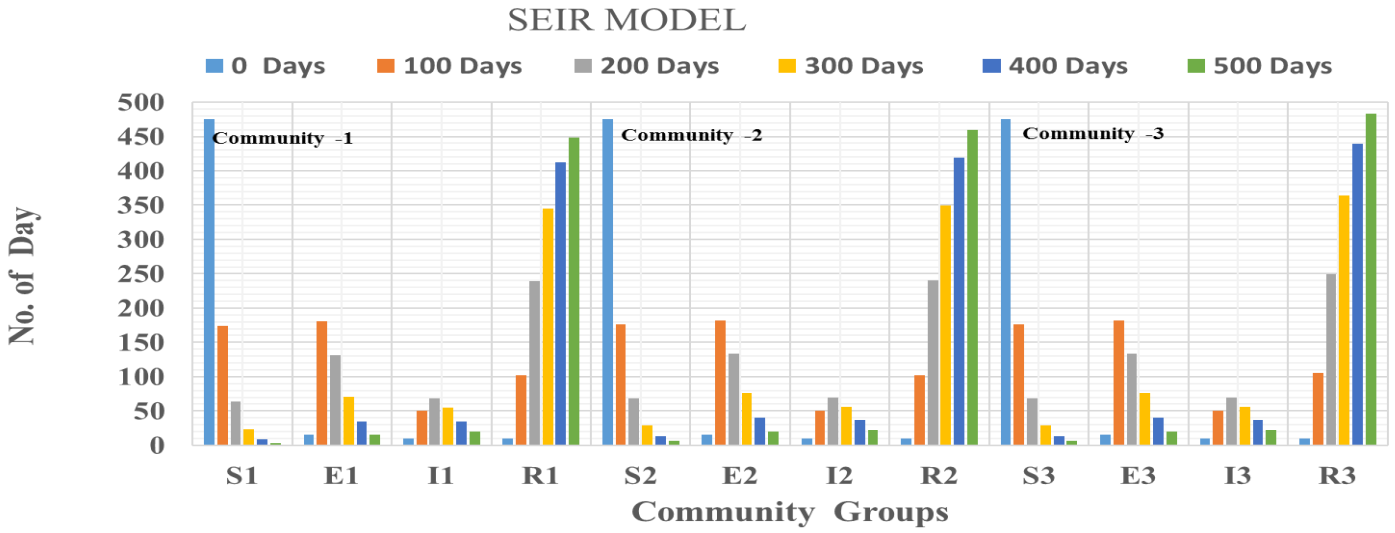


Figure 3.5: Community Distribution for SEIR-SEIR-SEIR Mapped Communities

3.5.3 *Community Distribution for SEIRS Mapped Communities*

Table 3.4: The Variation of SEIRS Distribution Vector with Time

	S1	E1	I1	R1	S2	E2	I2	R2	S3	E3	I3	R3
0 Days	475	15	10	10	475	15	10	10	475	15	10	10
100 Days	199	188	52	69	201	189	51	69	201	189	51	71
200 Days	138	167	75	121	143	170	76	121	146	171	76	127
300 Days	134	146	76	137	142	151	78	139	147	155	79	147
400 Days	136	139	73	137	146	147	75	141	154	152	77	151
500 Days	136	137	70	135	147	147	74	141	158	155	77	153

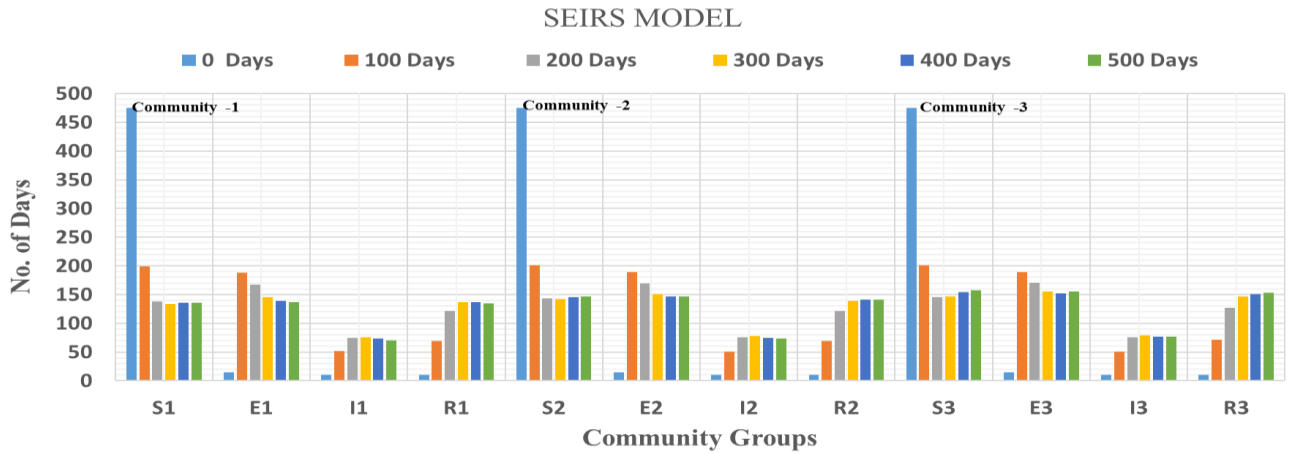


Figure 3.5: Community Distribution for SEIRS-SEIRS-SEIRS Mapped Communities

3.6 Control law for Mapped Community Epidemic

The dynamics of mapped epidemic can be modelled as state space equations:

$$\dot{X}(t) = AX(t) + BU(t)$$
$$Y(t) = CX(t) + DU(t) \quad (3.27)$$

where,

A is State Transition Matrix, B is input used to control epidemic, C denotes the output matrix, and D is transmission matrix.

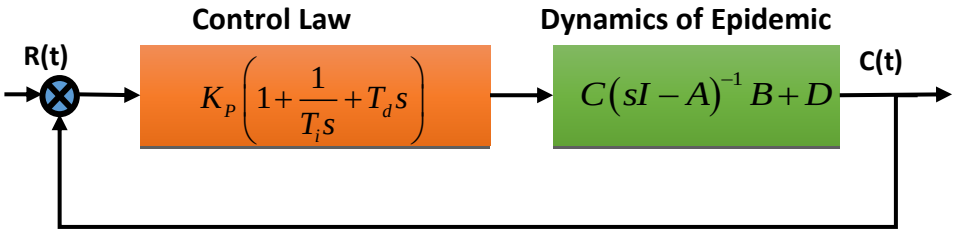


Figure 3.6: Control Law for Epidemic Dynamics

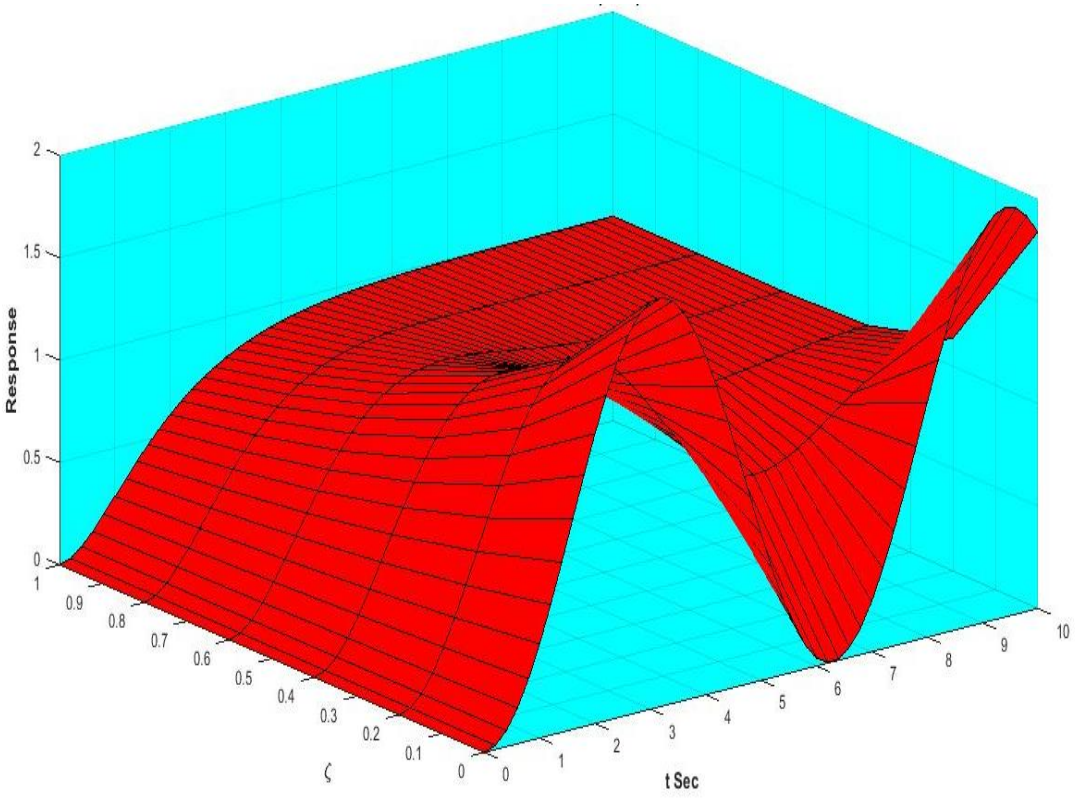


Figure 3.7: Transient Response of Local Epidemic After Control Law

For global epidemic:

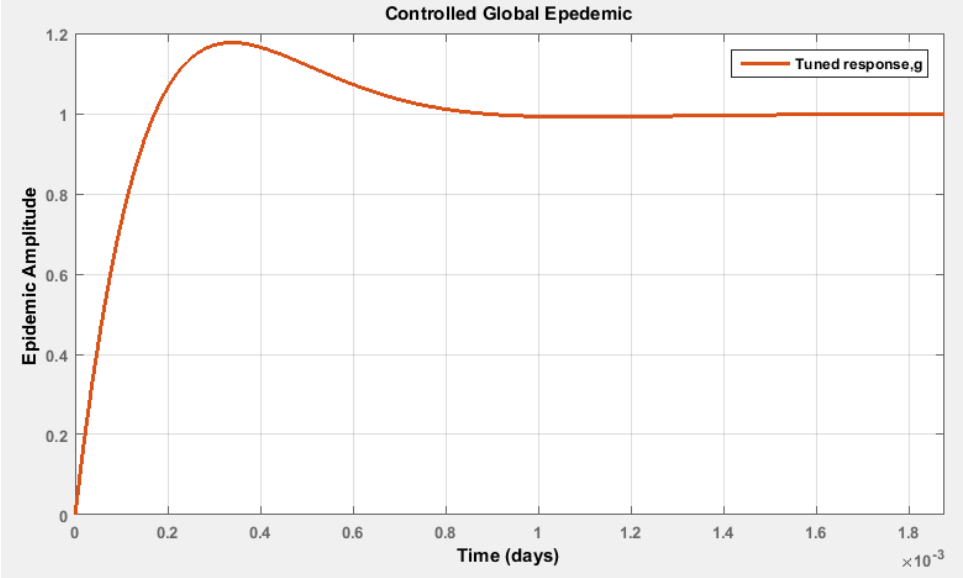


Figure 3.8: Transient Response of Global Epidemic After Control Law

3.7. *Results and Discussion*

The main aim of this research work is to map compatible epidemic model on any social contagion. The proposed work is implemented on various real time data sets and validated. Once the prediction of crisis migration is calculated using this model further diffusion of information which may lead to high degree crisis, can be controlled.

CHAPTER 4

CRISIS MANAGEMENT USING CENTRALITY AND CLUSTERING MEASUREMENT IN SOCIAL NETWORKS

4.1.*Introduction*

In this chapter an effort has been made to best control the spread of a crisis after an outbreak. The various metrics of the network have been formulated to prevent the dissemination of the crisis in the social network. The spread of the social contagion spreads from one community to another. It does not remain confined to one community, it infiltrates from local community to global community [24], [25], [26]. To prevent the dispersal of the crisis the elements which are instrumental in propagating the crisis need to identified and cleaved in the network. This can be achieved by identifying the nodes with highest centrality and excluding them from the network. They are identified after applying an algorithm and after that the nodes are cleaved from the network using modularity and spectral clustering algorithms [27]. The relationship and dependency of various critical metrics of the network like betweeness centrality, separation constant, isolation time and modularity are also analyzed with real time data.

The smallest social network is composed of only two actors and is called a dyad. A subset of three actors is called a triad. Actors between which ties can be made form a group and can be usually represented with a graph which is called a sociogram. A network is a set of nodes connected by a set of ties. These nodes can be anything, persons, individuals, teams, organizations, concepts, patents etc. In case of social networks, the nodes are individuals. The networks can be homogenous, which consists of similar nodes and heterogeneous, which are made up of dissimilar nodes. The ties can be directed, undirected, dichotomous or weighted [28]. When focus is on a single node, that node is termed as ego and the nodes it has ties with are called alters. The data collected by network analysis is relational data, which is

represented in matrix form or graphic form. The ways to represent network is graph, edge list and adjacency matrix.The basic concepts of social network analysis are network, tie strength, node strength and cohesion. Tie strength helps to identify whether the relation between the entities is strong or weak. It is denoted by the weight of the tie [29]. Edge weights signify the relationship strength in social networks.

Homophily leads to formation of clusters where formation of ties is easier. The drawback of this feature is that it does not promote any innovation or interaction between entities of diverse ideas [30], [31], [32], [33]. The power of central actors to control information flow, give advice and orders and influence economic outcomes comes from strategic structural position rather than from leadership capacities. In some situations, persons or entities attached to a network by a single link are totally dependent on that link to access resources from other networks. Because networks are dynamic it is assumed by social network analysis that actors develop strategies to alter the structure rather than the behaviour of the actors to their advantage. Network tactics are based on the principle that it is easier to influence someone who is close and present at the same tie. The probability of forming a tie is inversely proportional to the distance therefore propinquity is a fundamental of network strategies. The strong degree of embeddedness reflects trust between peers therefore reduces risks linked with any social or political activities. Strongly connected actors are considered central, repositories of information and channels of communication. With this advantage also lies a drawback that they lack brokerage which allows them to tap the information from the adjoining networks. Structural position of brokerage comes from its ability to access the resources and coordinate with an external network in the absence of a direct link with it [34], [35], [36].

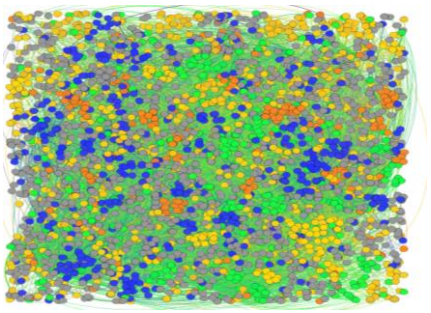
A very important feature of social networks is centrality. This helps us identify the key and central nodes in a network. There are four main categories of centrality - degree centrality, betweeness centrality, Eigen value centrality and closeness centrality. Degree centrality is a local measure of the number of ties a node or has in the network. Actors or nodes with a high degree of centrality are regarded as powerful actors as they are surrounded by many nodes and their range of influence is high [37]. Betweeness centrality refers to the importance of bridging disconnected nodes. The nodes with high betweeness centrality usually bridge actors which would otherwise not be connected. This property reflects the nodes that are communication links between less connected networks. Closeness centrality is a global way to determine how closely nodes are connected together. Actors with high closeness centrality

often refer to individuals like counsellors who have the ability to influence. Eigen Value Centrality indicates those nodes which are central because they are connected to other central actors [38].

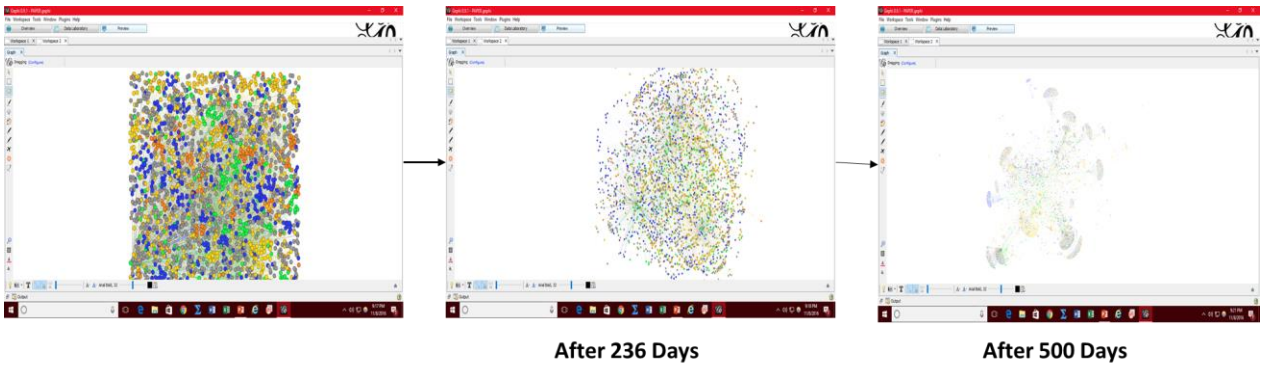
There are various measures by which we can characterize a network. Some of them are reciprocity, density and clustering. Reciprocity is a useful indicator of mutual exchange in a network which makes the network more cohesive. A network's density is a common measure of how closely knit is the network. It is a useful feature in comparing sub networks within a single large network. In this chapter the various clustering algorithms are used to identify the outgoing clusters of community.

4.2. *Role of Epidemic Mapping in Social Networks*

Diffusion of information across the social network exactly happen as the spread of epidemic, where some peoples act as susceptible, a few are infected or informed and a few are recovered. The dynamics of epidemic mapped social network is very important to predict the future scenario of a social network. The various epidemic models can be used to map in social networks as shown in Figure-4.1



(a)



(b)

Figure 4.1 SEIRS Mapped Social Networks, (a) Simulation in Gephi (b) Distribution with time

4.3. *Multilayer Epidemic Model mapping for Global Community*

The spread of information in a community in the form of epidemic does not remain in a closed system ever. After a period of time this information will diffused to other community and information will spread from local community to global community [39]. If the dynamics of information epidemic is known at any interval of time, then the high centrality elements carrying the information, can be excluded from the community in order to prevent the flaming. The high centrality element always found in I compartment of any epidemic model, leads to information diffusion in other community. The global community model is constructed from the local community epidemic model as shown in Figure 4.2.

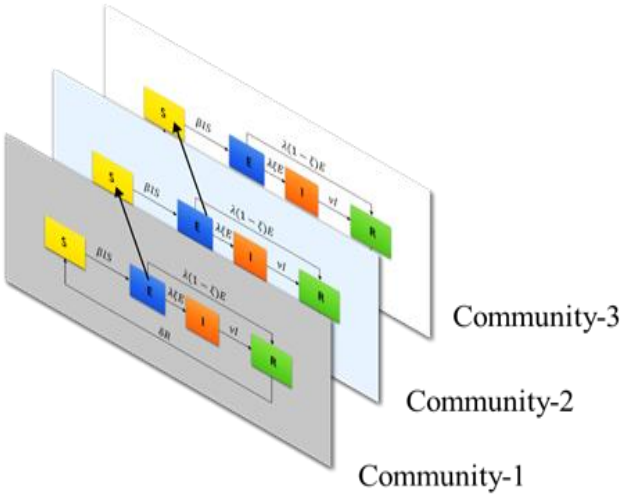


Figure 4.2: Global Community Formation From Multilayered Local Community

In order to know the real time dynamics of information spread the following algorithm is used:

Algorithm 4.1: Real time Dynamics prediction algorithm for information epidemic spread from local to global community

1. Express the community dynamics in terms of differential equations
2. Convert the local community to global community by using separation constant to calculate the spread flow rates in local and global community
3. Compute the state space matrix A:

$\beta, \nu, \lambda, \delta \leftarrow$ Information Flow rates

$\xi \leftarrow$ Separation Constant

$\lambda \leftarrow f(\xi)$\\Leadsto formation of global community

$[\dot{\beta} \quad \dot{\nu} \quad \dot{\lambda} \quad \dot{\delta}]^T = A[\beta \quad \nu \quad \lambda \quad \delta]^T$ \\ state space matrix A

4. $P \leftarrow f(A)$\\ from Kolmogorov Equations
5. real time dynamics of information spread

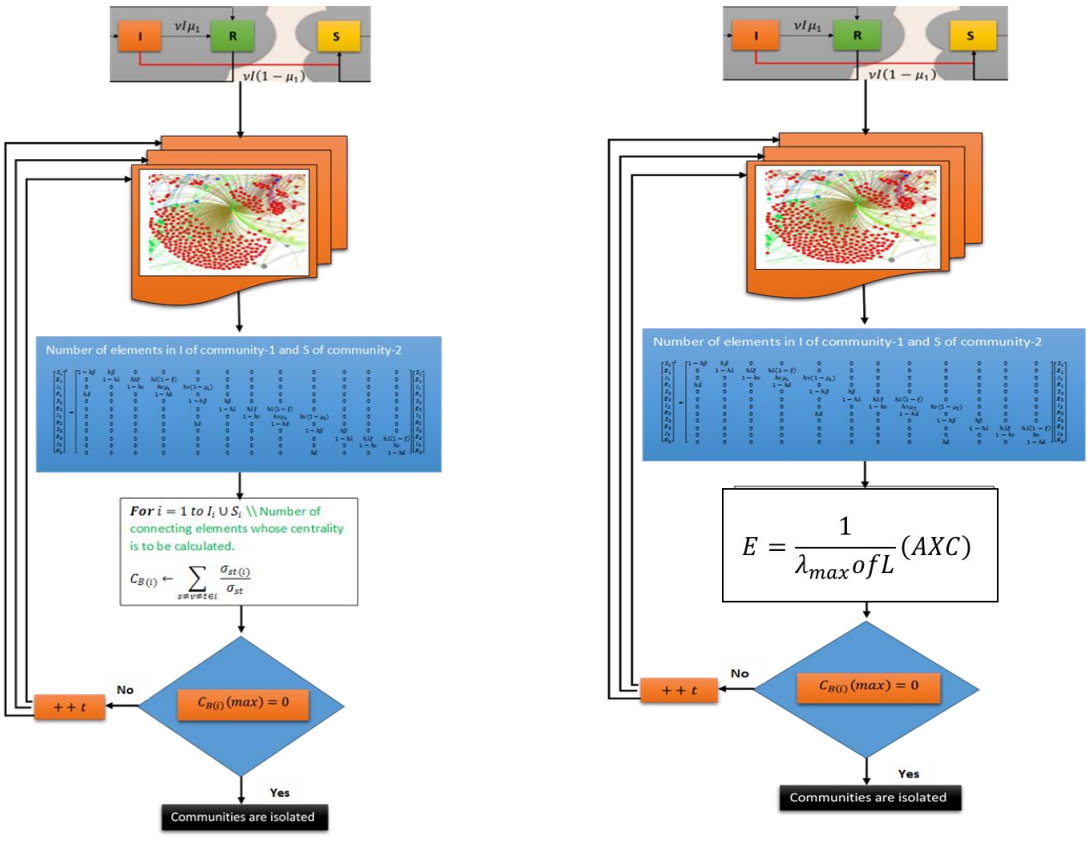
$S \leftarrow$Initial Distribution Vector

$S^t \leftarrow$ Distribution Vector at any time t

$S^t \leftarrow SP^t$ \\real time dynamics of information in SEIRS mapped social network.

4.4 *Algorithm to find high centrality element*

The local communities interact with each other through migration of infected individual from one community to other the prediction of persons in each community with the time can be calculated using algorithm 1. If the elements with high centrality between I compartment of one community and S compartment of other community is identified, then plugging out that element will isolate two communities to form global community. The following algorithm is to identify the high centrality element connecting two communities. The algorithm is described in the form of flow digraph, shown in the Figure 4.3.


I
R
S
Number of elements in I of community-1 and S of community-2
For $i = 1$ to $I_i \cup S_i$ \\ Number of connecting elements whose centrality is to be calculated.
$C_{B(i)} \leftarrow \sum \frac{\sigma_{st(i)}}{\sigma_{st}}$
No
$++t$
$C_{B(i)}(max) = 0$
Yes
Communities are isolated
$E = \frac{1}{\lambda_{max} ofL}(AXC)$

(a) (b)

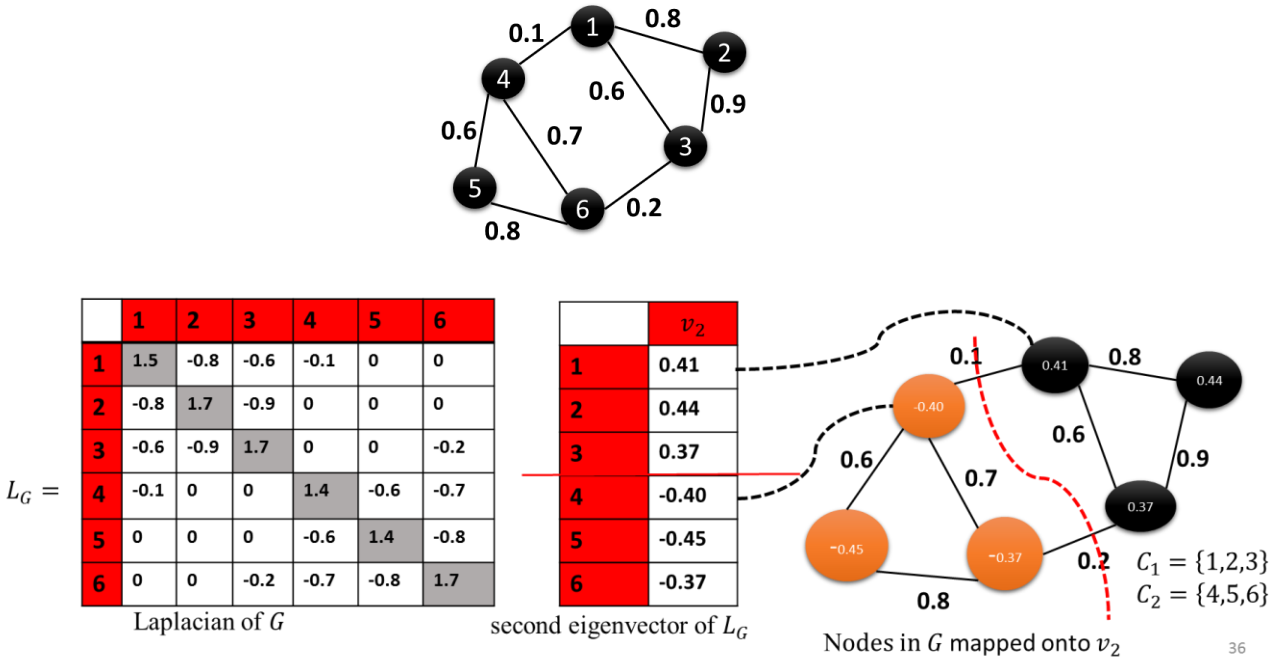
Figure 4.3: Algorithm to Identify the Element with High Centrality Connecting Two Communities (a) High Betweeness Centrality (c) High Eigenvecter Centrality

4.5. *Algorithm for Bi partitioning and k-Way Spectral Clustering*

To Find the bipartition, we take the second eigenvector of Laplacian, v_2, corresponding to λ_2, the algebraic connectivity of G.

1. The smaller λ_2 the better quality of partitioning
2. For each node i in G, assign it the value $v_2(i)$ e.g. $v_2(1)$=0.41 in G
3. To find the clusters C_1 and C_2 assign nodes with:

$v_2(i) > 0$ to C_1 and $v_2(i) < 0$ to C_2



	1	2	3	4	5	6
1	1.5	-0.8	-0.6	-0.1	0	0
2	-0.8	1.7	-0.9	0	0	0
3	-0.6	-0.9	1.7	0	0	-0.2
4	-0.1	0	0	1.4	-0.6	-0.7
5	0	0	0	-0.6	1.4	-0.8
6	0	0	-0.2	-0.7	-0.8	1.7

	v_2
1	0.41
2	0.44
3	0.37
4	-0.40
5	-0.45
6	-0.37

Figure 4.4:Bi partitioning via Spectral Clustering

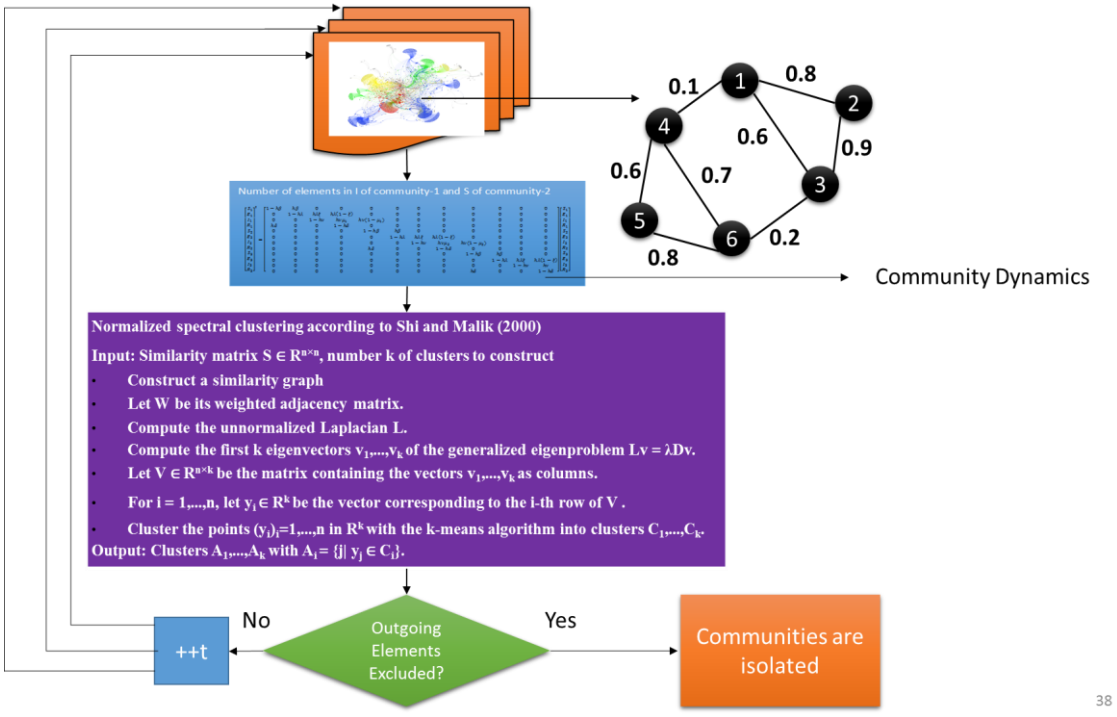

Number of elements in I of community-1 and S of community-2
Community Dynamics
Normalized spectral clustering according to Shi and Malik (2000)
Input: Similarity matrix S ∈ Rⁿˣⁿ, number k of clusters to construct
Construct a similarity graph
Let W be its weighted adjacency matrix.
Compute the unnormalized Laplacian L.
Compute the first k eigenvectors v1,...,vk of the generalized eigenproblem Lv = λDv.
Let V ∈ Rⁿˣᵏ be the matrix containing the vectors v1,...,vk as columns.
For i = 1,...,n, let yi ∈ Rᵏ be the vector corresponding to the i-th row of V .
Cluster the points (yi)i=1,...,n in Rᵏ with the k-means algorithm into clusters C1,...,Ck.
Output: Clusters A1,...,Ak with Ai = {j| yj ∈ Ci}.
++t
No
Outgoing Elements Excluded?
Yes
Communities are isolated
38

Figure 4.5:k-Way Spectral Clustering Algorithm

4.6. Algorithm for Modularity clustering

A measure of strength of division of a network into clusters or communities.

$$Q = \frac{1}{2m}\sum_{c}\sum_{i,j\in c}(A_{ij} - \frac{d_i d_j}{2m}) \qquad (4.1)$$

where i and j denotes nodes, c denotes clusters, is the (i,j) entry in adjacency matrix A . Degrees of 7 nodes are:

$$d = [3,3,3,4,3,2,2]^T$$

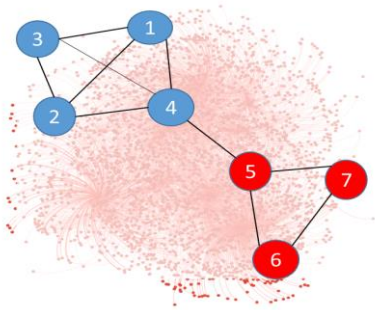
Total Degree:

$$2m = 20$$

The modularity matrix below has (i, j) entry:

$$A_{ij} - \frac{d_i d_j}{2m} \qquad (4.2)$$

i \ j	1	2	3	4	5	6	7
1	-0.45	0.55	0.55	0.4	-0.45	-0.3	-0.3
2	0.55	-0.45	0.55	0.4	-0.45	-0.3	-0.3
3	0.55	0.55	-0.45	0.4	-0.45	-0.3	-0.3
4	0.4	0.4	0.4	-0.8	0.4	-0.4	-0.4
5	-0.45	-0.45	-0.45	0.4	-0.45	0.7	0.7
6	-0.3	-0.3	-0.3	-0.4	0.7	-0.2	0.8
7	-0.3	-0.3	-0.3	-0.4	0.7	0.8	-0.2



Node 1, 2, 3, 4 tend to form one community and node 5, 6, 7 for another. The Modularity Q based on this division is the sum of all green cells in modularity matrix divided by 2m: 0.355

4.7. *Simulations and Results*

	S1	E1	I1	R1	S2	E2	I2	R2	S3	E3	I3	R3
0 Days	723	15	9	6	723	15	9	6	723	15	9	6
50 Days	446	231	33	41	447	232	33	42	447	232	33	42
100 Days	298	282	73	97	300	282	73	97	301	283	73	100
153 Days	227	270	78 | 22	148	232	273	101	148	134	273	101	152

$[S \quad E \quad I \quad R]^T = [S \quad E \quad I \quad R]{P_{G_3}}^T$

0 Days	232	273	101	148
50 Days	206	250	113	180
100 Days	200	231	115	197
122 Days	199	225	96 | 19	201

$[S \quad E \quad I \quad R]^T = [S \quad E \quad I \quad R]{P_{G_2}}^T$

0 Days	179	194	105	196
50 Days	186	190	101	197
100 Days	190	189	99	196
150 Days	192	190	97	194

$[S \quad E \quad I \quad R]^T = [S \quad E \quad I \quad R]{P_L}^T$

Community Isolation: FAST

No. of excluded Nodes: LARGE

Mapped Epidemic is: SEIRS

Network Dynamics: SLOW

Figure 4.6:Communities Isolation using Modularity clustering

	S1	E1	I1	R1	S2	E2	I2	R2	S3	E3	I3	R3
0 Days	723	15	9	6	723	15	9	6	723	15	9	6
50 Days	446	231	33	41	447	232	33	42	447	232	33	42
100 Days	298	282	73	97	300	282	73	97	301	283	73	100
217 Days	199	241	57 | 40 | 17	184	208	245	114	186	212	247	115	194

$[S \quad E \quad I \quad R]^T = [S \quad E \quad I \quad R]{P_{G_3}}^T$

0 Days	208	245	114	186
50 Days	203	229	116	200
100 Days	203	218	114	206
197 Days	205	211	54 | 42 | 17	206

$[S \quad E \quad I \quad R]^T = [S \quad E \quad I \quad R]{P_{G_2}}^T$

0 Days	228	225	114	224
50 Days	227	225	114	225
100 Days	226	226	113	226
150 Days	226	226	113	226

$[S \quad E \quad I \quad R]^T = [S \quad E \quad I \quad R]{P_L}^T$

Community Isolation: SLOW

No. of excluded Nodes: SMALL

Mapped Epidemic is: SEIRS

Network Dynamics: SLOW

Figure 4.7:Communities Isolation Communities Isolation using Spectral Clustering

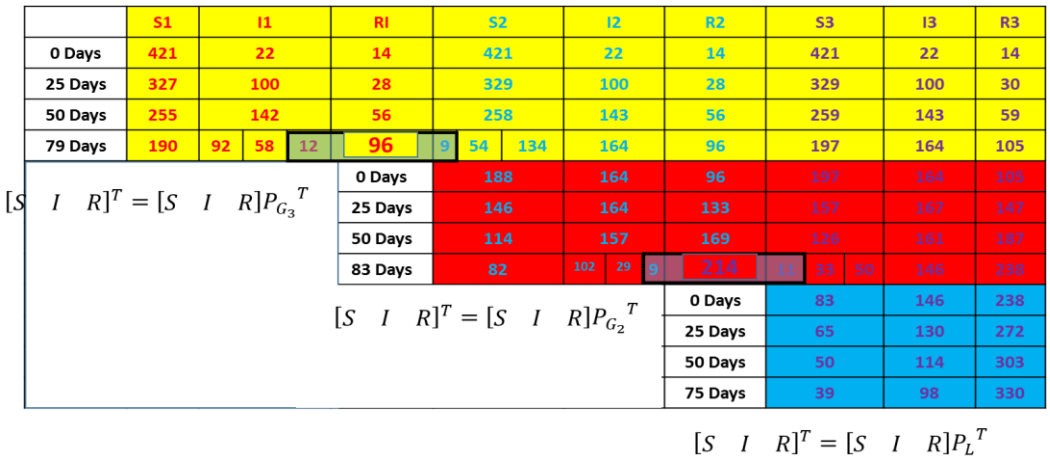


Figure 4.8: Communities Isolation using Betweeness Centrality

Betweeness Centrality:

The centrality of the node which lies on the connection or communication path and can control the flow of communication. This node is the bridging node between two clusters.

Eigenvector centrality:

This centrality denotes, which node is connected to the most of central nodes.

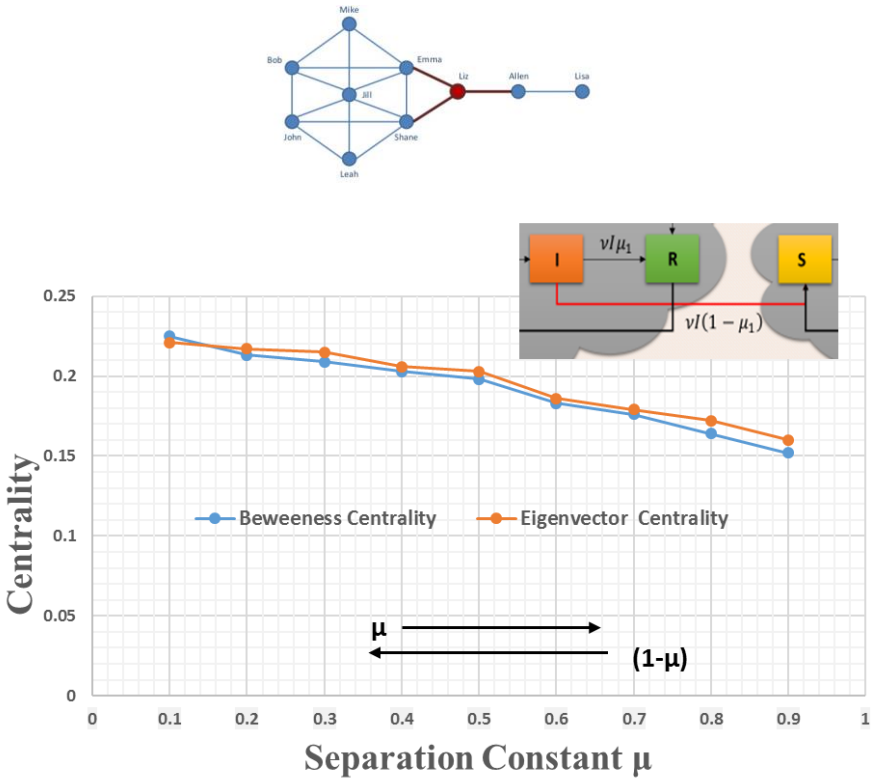


Figure 4.9: Dependency of Centrality Measurement with Separation Constant

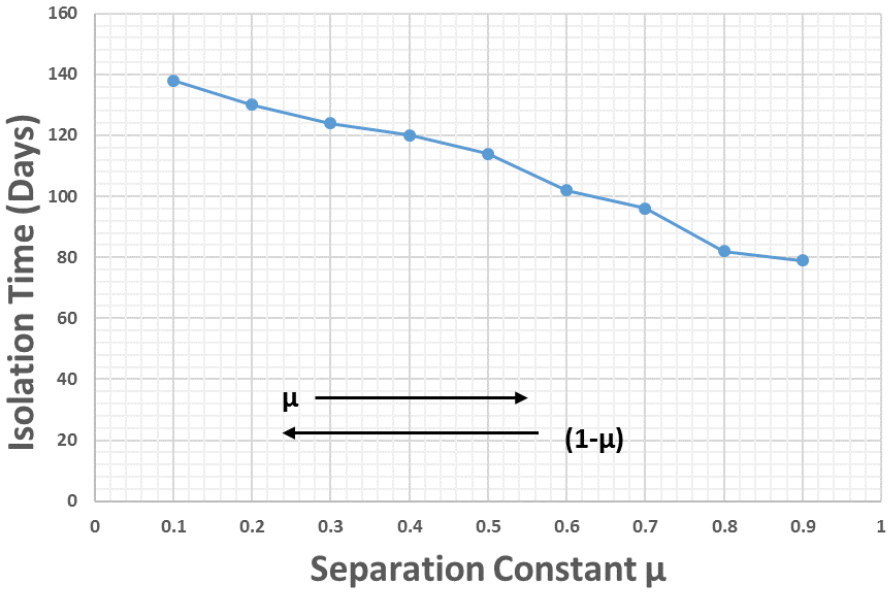


Figure 4.10: Variation of Isolation Time with Separation Constant

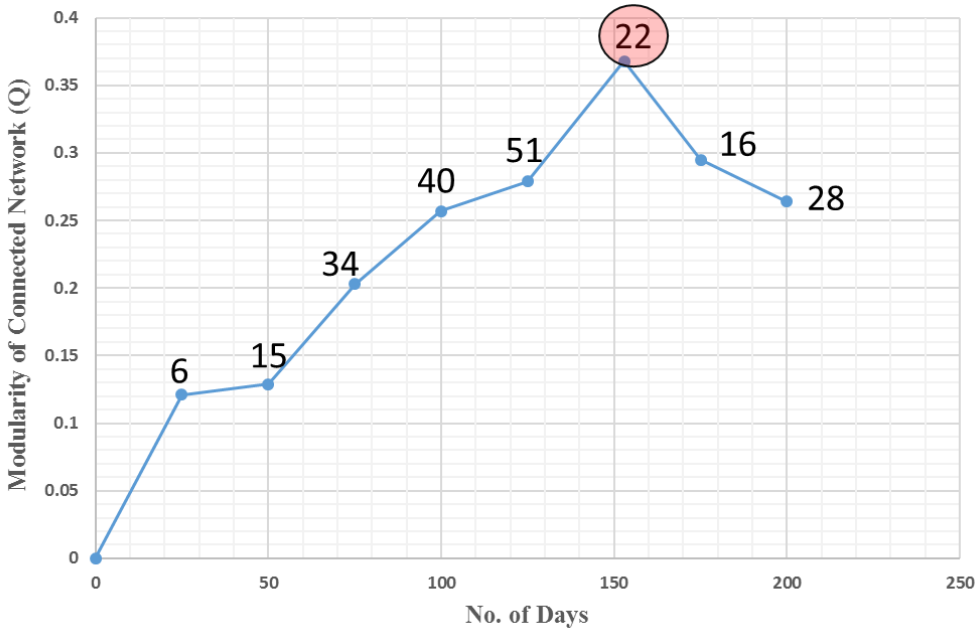


Figure 4.11: Isolation of Communities using Modular Clustering

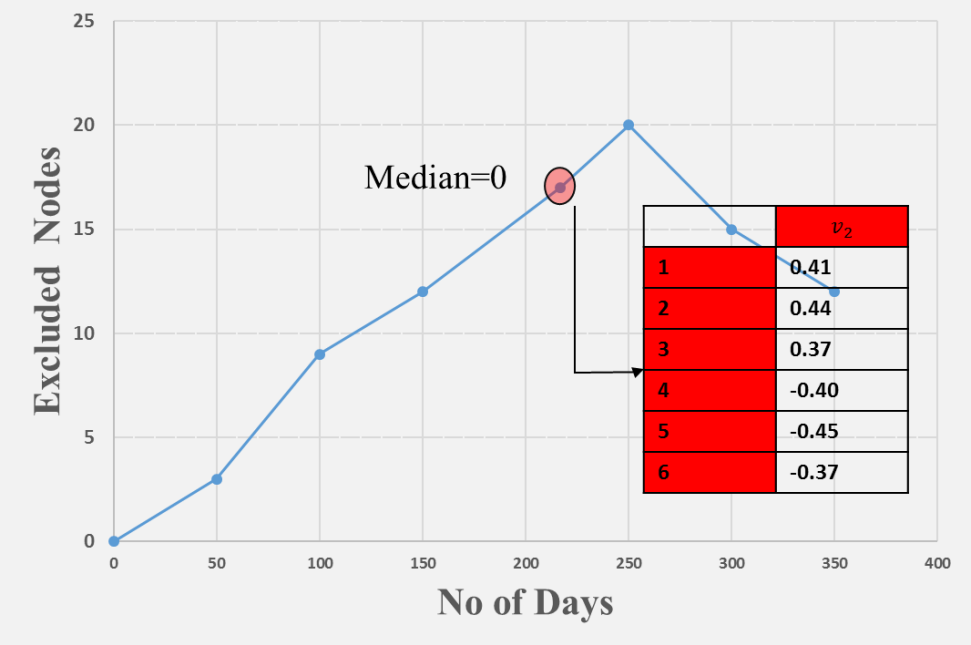


Figure 4.12: Isolation of Communities using Spectral Clustering

4.8.*Results and Discussion*

The introduction of social media and smart gadgets, has augmented the formation of social networks. High speed internet connectivity changes the dynamics of formed social network very fast. In such scenario, epidemic modeling of social network play very important role. In this chapter, we have proposed a model to predict of networking in social network analysis. This futuristic prediction can find out the element with high centrality connecting two communities. Excluding elements which are going to be a bridge between two communities, may prevent the occurrence of crisis. In future, this proposed model can be used with modularity centrality and eigenvector centrality.

CHAPTER 5

IDENTIFICATION OF SIMILAR COMMUNITIES CONNECTED IN A DENSELY CONNECTED SOCIAL NETWORKS

5.1.*Introduction*

The mathematical model discussed in this paper is very suitable for community identification. Once the community is identified, an individual control measure can be applied to each community. There are a few identifiable ways in which the information is treated when it communicated in the network, either it is retained, delayed or exaggerated etc. Depending on these factors, certain information processing elements are established in the network. Analogous to mechanics and electrical networks, social networks consist of building blocks termed as information processing elements. We have extracted the information processing elements. The transfer function of information flow digraph is derived using forward path gain and closed loop gain [39-45]. From the transfer function, canonical form of state space model is obtained. The similar eigen values replicate the similar characteristics of communities. The situation of crisis for control action is also predicted from these eigen values. If the eigen value corresponding to a community is negative, then the crisis can be controlled within the community.

5.2. *InformationProcessing Elements*

The information processing elements are classified as follows:

5.2.1 Restriction Element

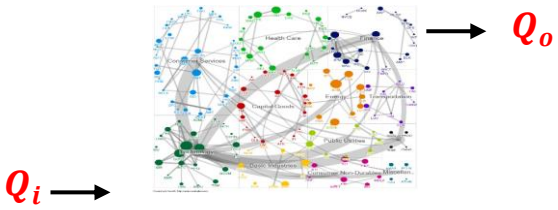


Figure 5.1: Restriction Element

$$G(S) = \frac{D}{Q_i} = R(5.1)$$

5.2.2 Flaming Element

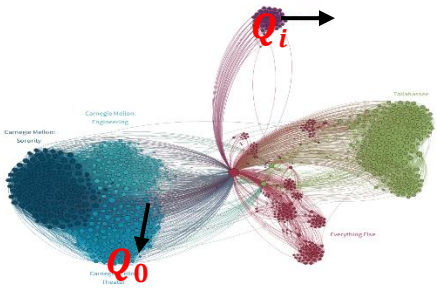


Figure 5.2: Flaming Element

$$G(S) = \frac{Q_0}{Q_i} = A \quad (5.2)$$

5.2.3 Harvesting Element

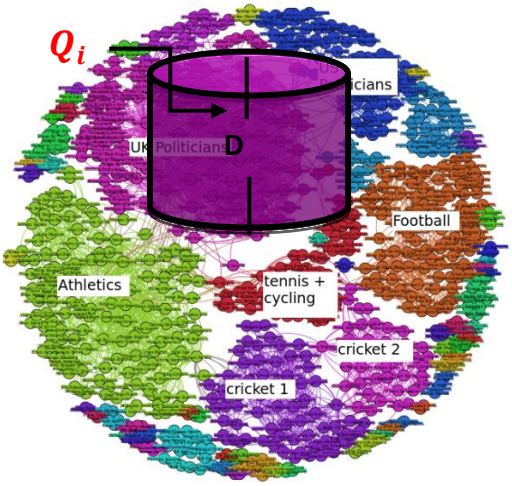


Figure 5.3: Harvesting Element

$$G(S) = \frac{D}{Q_i} = \frac{1}{CS} (5.3)$$

5.2.4 Delay Element

$$G(S) = \frac{D}{Q_i} = \frac{R}{(RCS+1)} = \frac{R}{(\tau S+1)} \quad (5.4)$$

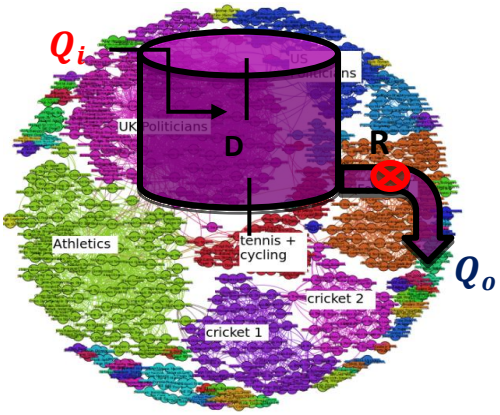


Figure 5.4: Information Delay Element

5.3 *Extracted Signal Flow Graph*

The Mason algorithm is used to compute the transfer function of extracted digraph

$T(s) = \frac{1}{\Delta}\sum_k P_k \Delta_k \quad (5.5)$

From figure 5.5, three loops are: $-a_1/s$, $-a_2/s^2$, and $-a_3/s^3$ and four forward path are: $b_0, b_1/s$, b_2/s^2, and b_3/s^3. Using Equation (5.5), the transfer function is:

$T(s) = \frac{b_0 + b_1/s + b_2/s^2 + b_3/s^3}{1-(-a_1/s - a_2/s^2 - a_3/s^3)}$ (5.6)

Equation (5.6) gives third order transfer function.

$T(s) = \frac{b_0\, s^3 + b_1\, s^2 + b_2\, s + b_3}{s^3 + a_1\, s^2 + a_2\, s + a_3}$(5.7)

For order n, (5.7) can be written in the form of :

$T(s) = b_0 + \sum_{i=1}^{n} \frac{c_i}{s-\lambda_i}$(5.8)

where c_i is pole's residue at$s = \lambda_i$.

The derived Jordan canonical form is:

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \vdots \\ \dot{x}_n \end{bmatrix} = \begin{bmatrix} \lambda_1 & 0 & 0 & \cdots & 0 \\ 0 & \lambda_2 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & & \vdots \\ 0 & 0 & 0 & \cdots & \lambda_n \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} + \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix} u \quad (5.9)$$

5.4. Derived Jordan Canonical Form

The transfer function of a 3rd order system is derived as:

$$T(s) = \frac{2s^2 + 6s + 7}{(s+1)^2(s+2)}$$

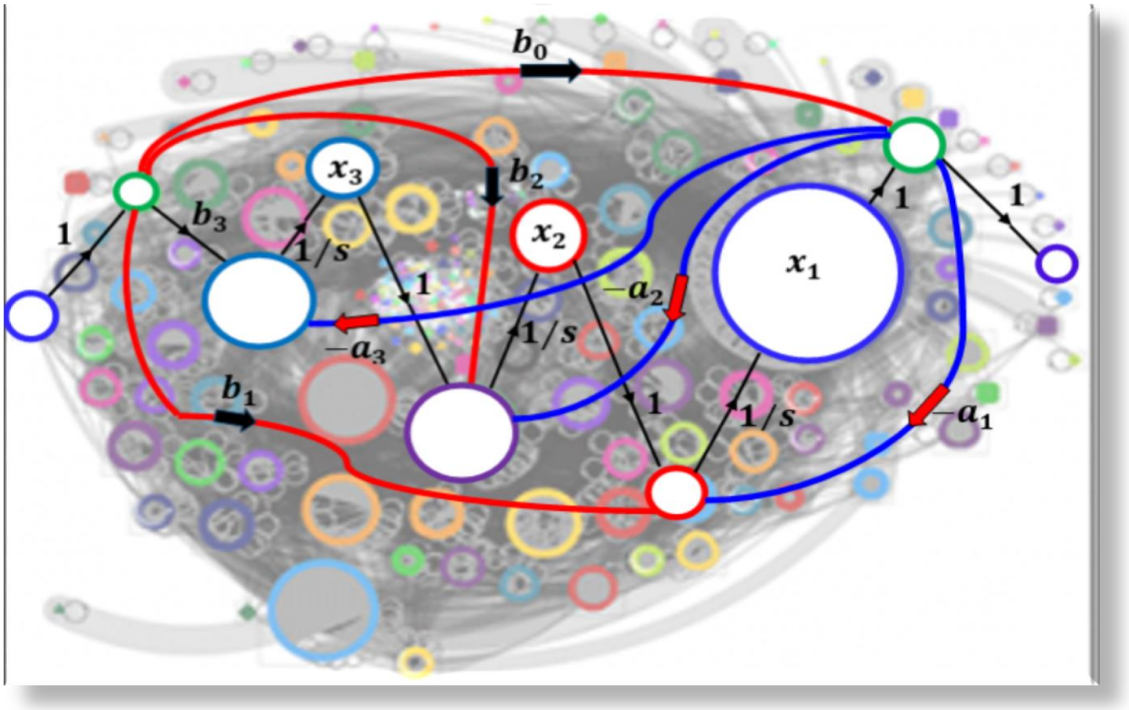
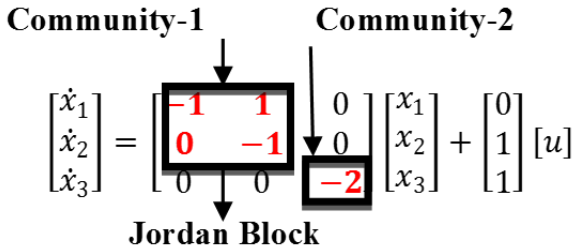


Figure 5.5: Established Information Flow Graph from Social Networks

Using Equation (5.8):

$$T(s) = \frac{-1}{(s+1)} + \frac{3}{(s+1)^2} + \frac{3}{(s+2)}$$

From Equation (5.9), the Jordon canonical form is:



$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \end{bmatrix} = \begin{bmatrix} -1 & 1 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & -2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix} [u]$$

$$y = [-1 \quad 3 \quad 3] \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$$

$$T(s) = \frac{-1}{(s+1)} + \frac{3}{(s+1)^2} + \frac{3}{(s+2)}$$

There are two repeated roots in this transfer function indicates two similar communities in the extracted network [55].

Algorithm 5.1: Control algorithm for social network crisis.

1. For community identification, break social network in the form of Jordan canonical model.
2. Check the possibility of crisis across each community:
$\boldsymbol{I_{Diff}}$ ← Information Diffusion Time
$\boldsymbol{F_{Peak}}$ ← Flaming Peak
$\boldsymbol{F_{Set}}$ ← Flaming Settling Time
$\boldsymbol{Com_{Un}}$ ← Uncorrected Community
$\boldsymbol{Com_{Sta}}$ ← Stable Community
3. Apply the control law:
Com← Identified Community
CL← Control Law

$\boldsymbol{If}(\text{Com} == I_{Diff} \uparrow \&\& F_{Peak} \uparrow \&\& Com_{Un} \uparrow \&\& Com_{Sta} \downarrow)$
$CL == K_p$ \\ Proportional Control

$\boldsymbol{Else}$
$\boldsymbol{If}(\text{Com} == I_{Diff} \uparrow \&\& F_{Peak} \downarrow \&\& \boldsymbol{F_{Set}} \downarrow \&\& Com_{Un} \uparrow \&\& Com_{Sta} \uparrow)$
$CL == K_p + \frac{K_i}{s}$ \\ Proportional Integral Control

$\boldsymbol{Else}(\text{Com} == I_{Diff} \uparrow \&\& F_{Peak} \uparrow \&\& \boldsymbol{F_{Set}} \uparrow \&\& Com_{Un} \uparrow \&\& Com_{Sta} \downarrow)$
$CL == K_p + \frac{K_i}{s} + K_d$ s \\ Proportional Integral and Derivative Control

.

5.5. *Results and Discussion*

It is very critical to identify the communities with similar characteristics. The proposed algorithm in this chapter can be used to identify the similar communities corresponding to their eigenvalues. The prediction of situation under control, can also be done by using eigen values. The various parameters lead to crisis are discussed in algorithm. The same algorithm can be used for multiple information flow digraph in a same social network. The proposed algorithm can further extend to decoupling of multiple information flow digraph in a social network.

CHAPTER 6

CASE STUDY: NATURE OF COMMUNICATION IN SOCIAL NETWORKS

6.1.*Introduction*

Though we have ascribed many benefits to online communication, there is a flip side emerging to it in the form of online aggressive behavior. Now days social networking sites are becoming a platform for business users for creating contacts, finding buyers and sellers, hosting a commercial profile and others activities to promote their businesses. Therefore, it is very important to keep the hostile users away from the online platform to maintain a healthy communication environment and promote business negotiations. This paper, presents a model which will notify the presence of flaming in online communication and block the users who indulge in flaming during online business negotiations. Computer mediated communication has connected the globe in such a way that today the whole world connects with a common thread. It has broken all cultural, social, religious and geographic barriers bringing the world at a zero-distance level. Unfortunately, among its innumerable advantages, online communication has developed a darker side to it called flaming. With the freedom that online communication offers, the users have started infiltrating conversation with hostile and offensive exchange of words. Due to the absence of face to face interaction, there are various factors such as anonymity, lack of familiarity, absence of social cordiality and etiquettes that promote flaming. This study takes a look at the social context in which flaming occurs. This paper involves a study conducted on one subject in a confined environment. It focuses on the flaming tendencies and patterns. An effort is done to analyze the factors that affect flaming. The response of the online users on current and controversial issues is recorded. It is generally the sensitive issues that attract flaming. Also non-met friends have a tendency to shed their inhibitions and involve blatantly in flaming. Another observation is that the male gender has more inclination towards flaming and involves more in contemptuous comments. The Probit Model is used to analyze the recorded responses and draw the conclusions.

6.2. *Flaming in Social Networking Sites and Flame Detector Tool*

Social Networking Sites (SNS) were used to contact acquaintances, colleagues, friends and relatives but with the advances in website design, people also started to interact with strangers through these sites. Out of these stranger's research has also shown that males have a greater tendency to flame than female participants. Further, SNS are the places where the user can do all its gossips with their relatives as well as with their friends and might also do negotiation with the other business organizations. Today the popularity of SNS has increased immensely because it serves as a common platform for users to do diverse activities. Some users use it as a medium of self-expression, others use is for social networking while still others use if for business communication and negotiation the augmented communication of Internet made social networking site very fashionable.

6.3. *Results and Discussion*

The convenience and advantages of computed mediated communication is evident to one and all. However, as all boons have a flip side to them it is getting infiltrated with hostile and aggressive exchange of words. To keep the immense utility of online communication intact, it is essential to prevent it from getting adulterated with aggression and online misbehavior. This paper presents a security negotiation model which flags the presence of flaming in online communication and blocks flamers from business communication and negotiations.

CHAPTER7

CONCLUSION AND FUTURE SCOPE

The introduction of social media and smart gadgets, has augmented the formation of social networks. High speed internet connectivity changes the dynamics of formed social network very fast. Therefore, epidemic modeling of social network play very important role.

The proposed work in this thesis is motivated from the various researchers, who have also used the epidemic models for social network analysis. The main novelty of this thesis is to introduce a probabilistic model which can predict the degree and impact of crisis occurred in a social community, with the passage of time.

In this research, we have proposed a model to predict of networking in social network analysis. This futuristic prediction can find out the element with high centrality connecting two communities. Excluding element which is going to be a bridge between two communities, may prevent the occurrence of crisis. In future, this proposed model can be used with modularity centrality and eigenvector centrality.

The last contribution towards the thesis is, identification of similar communities in a social network. These identified communities can be clustered together and tagged to single community.

The future scope of this research is to integrate the two most upcoming fields, Internet of Things and Social Network Analysis. Since each human and machine is integrated with IP enabled devices, various open issues can be addressed in the form of new research.

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LIST OF PUBLICATIONS

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2. Ruchi Verma, Vivek Kumar Sehgal and Nitin, "Computational Stochastic Modeling to Handle the Crisis Occurred During Community Epidemic", Annals of Data Science, Springer, volume 3, Issue 2, pp 119–133.doi:10.1007/s40745-016-0075-y.

3. Ruchi Verma, Nitin and Amit Srivastava, "On Behavioral Responses and Different Shades of Flaming in Social Media and Computer Mediated Communication", International Journal of Human Capital and Information Technology Professionals, IGI Global, Volume 7, Issue 4, 2016, pp. 33-49, DOI: 10.4018/IJHCITP.2016100103 **[Scopus Indexed Journal].**

4. Ruchi Verma, Vivek Kumar Sehgal and Nitin, "Implementation of Control Measure in the Crisis Using Social Networks", International Journal of Simulation Systems, Science & Technology, ISSN 1473-804x, UK Vol. 17 Issue 32, pp. 11.1-11.7. DOI 10.5013/IJSSST.a.17.32.11 [**Scopus Indexed Journal] .**

5. Ruchi Verma, Vivek Kumar Sehgal and Nitin, "Implementation of Information System in Crisis Management Using Modeling and Simulation", International Journal of Simulation Systems, Science & Technology, ISSN 1473-804x, UK, Vol. 17 Issue 32, pp. 12.1-12.10. DOI 10.5013/IJSSST.a.17.32.12. **[Scopus Indexed Journal].**

6. Ruchi Verma, Vivek Kumar Sehgal and Nitin, "Crisis Management Using Centrality Measurement in Social Networks"International Journal of Mobile Computing and Multimedia Communications (IJMCMC). **Accepted [Scopus Indexed Journal]**.